**CHAPTER TWO**

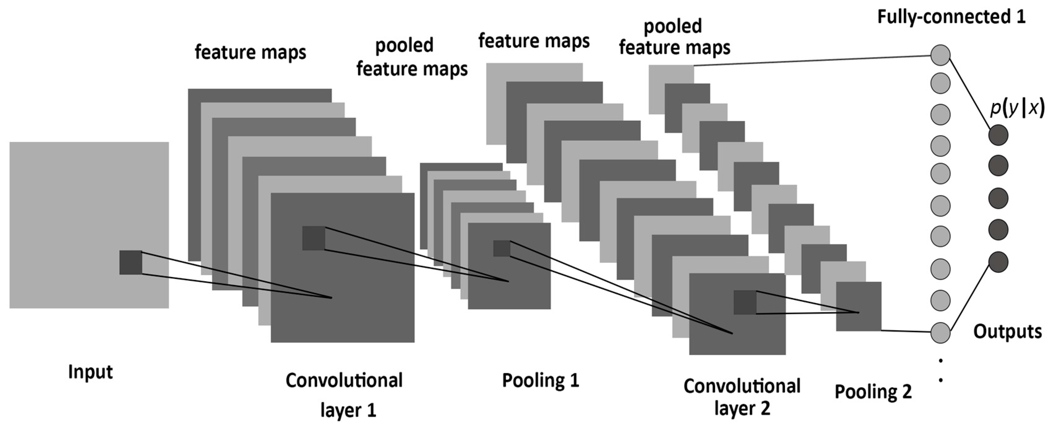
**LITERATURE REVIEW**

* 1. **BACKGROUND**

Plant diseases pose a significant threat to global food security, leading to considerable yield losses and economic hardship. Traditional detection methods, such as visual inspections by experts and laboratory testing, are not only time-consuming but also require specialized knowledge, making them less efficient for large-scale agricultural use (Agrios, 2005). With the growing demand for more reliable and rapid detection techniques, artificial intelligence (AI) and deep learning (DL) have emerged as promising solutions for automating plant disease diagnosis (Kamilaris and Prenafeta-Boldú, 2018). Machine learning (ML) has proven effective in predictive analysis and decision-making without explicit programming. Among ML techniques, deep learning especially in the field of image recognition has demonstrated remarkable success in plant disease detection (LeCun et al., 2015). Convolutional Neural Networks (CNNs), a key deep learning architecture, have been widely applied to analyse plant images, extract disease patterns, and classify infections with high accuracy (Krizhevsky et al., 2012). This chapter highlights studies that have contributed to advancements in plant disease detection while also discussing their potential improvements and challenges associated with real-world deployment.

* 1. **Fundamentals of Machine Learning**
* **Supervised Learning**: Models are trained using labeled datasets, where inputs are paired with corresponding outputs (Russell & Norvig, 2010).
* **Unsupervised Learning**: Models analyze unlabeled data to identify patterns, commonly applied in clustering (Goodfellow et al., 2016).
* **Semi-Supervised Learning**: Combines labeled and unlabeled data to enhance learning efficiency.
* **Reinforcement Learning**: It learns through interactions with environments which receives penalties based on actions
  + 1. **CNN Structure and Functionality**

The convolutional layer is the foundational component for feature extraction in CNNs, operating by sliding a filter across the input image, performing a convolution operation (Fukushima, 1980). Key hyperparameters like depth, stride, and zero-padding control the output volume's size and properties. Pooling layers, such as max pooling and average pooling reduce dimensionality which still retains essential information from feature maps by aggregating their features. Finally, the fully connected layer connects neurons from previous layers to produce classification outputs (He et al., 2016), with each neuron connected to all activations from the previous layer.



**Figure 2.1: Fully connected CNN Structure. (Mahmood & Albelwi, 2017)**

* 1. **Historical Research**
     1. **Deep Learning for Plant Disease Detection in Maize and Cassava: A Review of Key Studies**
        1. **Model Architectures**
* Craze et al. (2022) used a modified VGG16 model (GLS\_net) to detect Gray Leaf Spot (GLS) in maize, working with 18,656 images after augmentation but did not specify a deployment platform.
* Dosset et al. (2024) developed a MobileNetV3Small-based model (CDDNet) for cassava diseases, designed for edge devices but did not specify dataset size.
* O'Halloran et al. (2024) tested EfficientNet V2 B0, LeNet-5, VGG-16, and ResNet50 for detecting Maize Lethal Necrosis (MLN) and Maize Streak Virus (MSV) using 15,344 images, but no implementation platform was specified.
* Ramcharan et al. (2017, 2018, 2019) conducted multiple studies using Inception v3 with transfer learning, CNNs, and Single Shot Multibox Detector (SSD) with MobileNet for cassava disease detection, working with datasets ranging from 720 to 15,000 images, all deployed on mobile devices.
* Riaz et al. (2022) used EfficientNetB3 for Cassava disease classification with 21,397 images, also optimized for mobile deployment.
  + - 1. **Model Accuracy and Performance Analysis**
* O'Halloran et al. (2024) reported the highest accuracy (99.99%) using EfficientNet V2 B0 for detecting Maize Lethal Necrosis (MLN) and Maize Streak Virus (MSV).
* Ramcharan et al. (2017) reached 98% accuracy for Brown Leaf Spot and Cassava Brown Streak Disease using Inception v3 with transfer learning.
* Dosset et al. (2024) achieved 97.03%–98.95% accuracy across different cassava disease datasets with their MobileNetV3Small model (CDDNet).
* Craze et al. (2022) reported lower accuracy levels of 73.4%–78.6% for detecting Gray Leaf Spot in maize using a modified VGG16 model.
* Ramcharan et al. (2019) observed a significant drop in accuracy from 80.6% to 43.2% when detecting mild disease symptoms, highlighting challenges in real-world deployment.
* Ramcharan et al. (2018) noted a 32% decrease in F1 score when transitioning from controlled lab conditions to field testing.
* Riaz et al. (2022) reported an overall accuracy of 83.03%, exceeding 90% for certain disease classifications.
  + - 1. **Processing Speed and Resource Constraints**
* Ramcharan et al. (2019) was one of the few studies that reported inference times, ranging from 50 to 200 milliseconds.
* Dosset et al. (2024) described their MobileNetV3Small-based model as lightweight, but did not specify memory or computational resource usage. Other studies did not provide explicit data on processing speeds or model resource constraints.
  + - 1. **Disease-Specific Model Performance and Real-World Validation**
* Gray Leaf Spot (Maize): Modified VGG16 (GLS\_net) by Craze et al. (2022), with 73.4%–78.6% accuracy (no real-world validation).
* Maize Lethal Necrosis (MLN) & Maize Streak Virus (MSV): EfficientNet V2 B0 by O'Halloran et al. (2024), achieving 99.99% accuracy (no real-world validation).
* Cassava Brown Streak Disease: Inception v3 by Ramcharan et al. (2017), with 98% accuracy (real-world accuracy: 80.6%).
* Cassava Mosaic Disease: Inception v3 by Ramcharan et al. (2017), reaching 96% accuracy (no real-world validation).
* Cassava Green Mottle: No specific best-performing model found (accuracy unknown).
* Brown Leaf Spot (Cassava): Inception v3 by Ramcharan et al. (2017), with 98% accuracy (no real-world validation).
* Green Mite & Red Mite Damage (Cassava): Inception v3 by Ramcharan et al. (2017), achieving 95%–96% accuracy (no real-world validation).
* Only one study (Ramcharan et al., 2017) validated real-world performance (Cassava Brown Streak Disease, 80.6% accuracy).
  + - 1. **Challenges and Implementation Considerations**
* Environmental Variability: Ramcharan et al. (2018, 2019) reported that lighting, camera angles, and background complexity significantly affected model performance.
* Disease Severity: Ramcharan et al. (2019) observed that mild disease symptoms were harder to detect, reducing accuracy from 80.6% to 43.2%.
* Background Complexity: Craze et al. (2022) tested background removal but found no significant improvement in accuracy.
* Processing Speed: Only Ramcharan et al. (2019) provided inference speed details, reporting 50–200 milliseconds per image.
* Resource Constraints: Dosset et al. (2024) described their model as lightweight, but most studies lacked memory and energy usage details.
  + - 1. **Implementation Consideration**
* **Real-world Performance:** Ramcharan et al. (2018, 2019) provide insights into challenges of mobile deployment. Their studies show a reported drop in performance when models are used in real-world conditions. F1 scores reportedly decreased by 32% for pronounced symptoms in real-world conditions.
* **Processing Speed:** Ramcharan et al. (2019) reports specific inference times (50 to 200 ms) for their mobile-deployed model. I didn't find processing speed information for the other studies.
* **Resource Constraints:** Several studies mention developing” lightweight” models suitable for mobile devices (e.g., Dosset et al., 2024).
* **Usability:** Riaz et al. (2022) mention developing a graphical user interface to make their model more accessible.
  + - 1. **Literature Review on my dataset Source (CCMT)**
* Wulnye et al. (2024)​ achieved 94.60% accuracy using a CNN model optimized through quantization, enabling real-time classification on a microcontroller, while Chowdhury et al. (2024)​ reported 61.60% accuracy for maize classification in which he worked on ResNet, VGG and MobileNet, highlighting the need for data augmentation and hyperparameter tuning. In terms of processing speed and resource constraints, Wulnye et al. (2024) optimized their model to 321 KB, ensuring efficient deployment on Arduino Nano 33 BLE Sense, whereas Chowdhury et al. (2024) did not specify resource limitations but faced accuracy challenges. Regarding disease-specific model performance and real-world validation, Wulnye et al.’s model performed well across different maize diseases, whereas Chowdhury et al. (2024) identified low classification accuracy for some crops, including maize. Challenges and implementation considerations from both studies include dataset quality, environmental variability, and mobile deployment feasibility, with Wulnye et al. (2024) demonstrating real-time feasibility on edge devices. Finally, in implementation considerations, Wulnye et al. (2024) successfully deployed their model for real-time field use, while Chowdhury et al. (2024) emphasized the need for further optimization and validation to improve practical applicability.
  + - 1. **Influence of existing models on my related work**

Wulnye et al. (2024) demonstrate that their lightweight CNN model, optimized through model compression and quantization, achieves high accuracy for real-time deployment on resource-constrained devices. In contrast, Chowdhury et al. (2024) suggest that exploring architectures such as ResNet and MobileNet could further improve performance, though their findings, effective data preprocessing and augmentation are critical for achieving robust results. With these insights, my research would benefit from optimizing a CNN model and other model stated to develop accuracy and for real-time use with augmentation techniques to enhance maize disease classification accuracy.

* + - 1. **Factors Affecting Real-world Performance**
* Environmental Variability
* Disease Severity
* Data Quality and Diversity
* Model Architecture and Light weight Models
* Lightening and Weather Condition
  1. **Research Gaps and Direction**

Developing advanced data augmentation methods, leveraging pre-trained models, and exploring model compression techniques can improve model performance. However, real-world deployment poses challenges, as models often experience a significant drop in accuracy. For example, Ramcharan et al. (2018) observed a 32% decrease in F1 score when transitioning from laboratory to field environments, and Ramcharan et al. (2019) found a drop in classification accuracy from 80.6% to 43.2% for mild disease symptoms. To improve farmer adoption, incorporating explainable AI techniques, such as attention mechanisms, saliency maps, Internet of Things (IOT) sensors, is essential to help understand model decisions and patters, other researchers who want to work further on similar studies could look into future gaps.

* 1. **Conclusion**

Deep learning has shown great potential for automating plant disease detection in maize and cassava. While these models perform well in controlled environments, real-world challenges such as environmental variability, disease severity, and mobile deployment limitations remain. To improve real-world applicability, future research should focus on enhancing model generalization, computational efficiency, and explainability.

**References**

* Agrios, G.N. (2005) Plant Pathology. 5th edn. Amsterdam: Elsevier.
* Chowdhury, M.T., Hossain, M.J., Adnan, O.R., Sumon, M.I., Hossain, M.S., Rahman, H., Tagwar, M., Zarif, F.I., Ipty, S.I., Methila, M.K. and Runa, R. (2024) 'Detecting crop pests and diseases through deep learning techniques for improved yields', Proceedings of the 2024 International Conference on Artificial Intelligence and Data Science. Springer. DOI: 10.1007/978-981-97-3594-5\_39.
* Craze, H.A., Pillay, N., Joubert, F. and Berger, D. (2022) 'Deep learning diagnostics of gray leaf spot in maize under mixed disease field conditions', Plants, 11(6), pp. 1–16.
* Dosset, A., Dang, L., Alharbi, F., Habib, S., Alam, N., Park, H.Y. and Moon, H. (2024) 'Cassava disease detection using a lightweight modified soft attention network', Pest Management Science, 80(3), pp. 1–12.
* Fukushima, K. (1980) 'Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position', Biological Cybernetics, 36(4), pp. 193–202.
* Goodfellow, I., Bengio, Y. and Courville, A. (2016) Deep Learning. Cambridge, MA: MIT Press.
* He, K., Zhang, X., Ren, S. and Sun, J. (2016) 'Deep residual learning for image recognition', Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV: IEEE Computer Society Press, pp. 770–778.
* Kamilaris, A. and Prenafeta-Boldú, F.X. (2018) 'Deep learning in agriculture: A survey', Computers and Electronics in Agriculture, 147, pp. 70–90. Available at: https://www.sciencedirect.com/science/article/pii/S0168169917308803 (Accessed: 8 March 2025).
* Krizhevsky, A., Sutskever, I. and Hinton, G.E. (2012) 'ImageNet classification with deep convolutional neural networks', Advances in Neural Information Processing Systems, Lake Tahoe: Curran Associates Inc Press.
* LeCun, Y., Bengio, Y. and Hinton, G.E. (2015) 'Deep learning', Nature, 521(7553), pp. 436–444.
* Mahmood, A. and Albelwi, S. (2017) 'Deep learning for security of Internet of Things (IoT)', 2017 8th International Conference on Information Technology (ICIT), Amman, Jordan, pp. 241–246.
* Mensah Kwabena, P., Akoto-Adjepong, V., Adu, K., Ayidzoe, M.A., Asare Bediako, E., Nyarko-Boateng, O., Boateng, S., Donkor, E.F., Bawah, F.U., Awarayi, N.S., Nimbe, P., Nti, I.K., Abdulai, M., Adjei, R. and Opoku, M. (2023) 'Dataset for Crop Pest and Disease Detection', Mendeley Data, V1. Available at: https://doi.org/10.17632/bwh3zbpkpv.1 (Accessed: 5 February 2025).
* Nair, V. and Hinton, G.E. (2010) 'Rectified linear units improve restricted Boltzmann machines', Proceedings of the 27th International Conference on Machine Learning (ICML-10), Haifa, Israel: Omnipress, pp. 807–814.
* O'Halloran, T., Obaido, G., Otegbade, B. and Mienye, I.D. (2024) 'A deep learning approach for maize lethal necrosis and maize streak virus disease detection', Machine Learning with Applications, 15, p. 100476.
* Ramcharan, A., Baranowski, K., McClowsky, P., Ahmed, B., Legg, J. and Hughes, D.P. (2017) 'Deep learning for image-based cassava disease detection', Frontiers in Plant Science, 8, p. 1852.
* Ramcharan, A., McCloskey, P., Baranowski, K., Mbilinyi, N., Mrisho, L., Ndalahwa, M., Legg, J. and Hughes, D.P. (2019) 'A mobile-based deep learning model for cassava disease diagnosis', Frontiers in Plant Science, 10, p. 1425.
* Ramcharan, A., McCloskey, P., Baranowski, K., Mbilinyi, N., Mrisho, L., Ndalahwa, M., Legg, J. and Hughes, D.P. (2018) 'Assessing a mobile-based deep learning model for plant disease surveillance', arXiv preprint, arXiv:1811.08060.
* Riaz, S.M., Ahsan, M. and Akram, M. (2022) 'Diagnosis of cassava leaf diseases and classification using deep learning techniques', 2022 16th International Conference on Open-Source Systems and Technologies (ICOSST), Lahore, Pakistan, pp. 141–146.
* Russell, S.J. and Norvig, P. (2010) Artificial Intelligence: A Modern Approach. 3rd edn. Upper Saddle River, NJ: Prentice Hall.
* Wulnye, F.A., Asiedu, D.K.P., Arthur, E.A.E., Wilson, M., Gookyi, D.A.N. and Agyemang, J.O. (2024) 'TinyML implementation on microcontrollers: The case of maize leaf disease identification'.